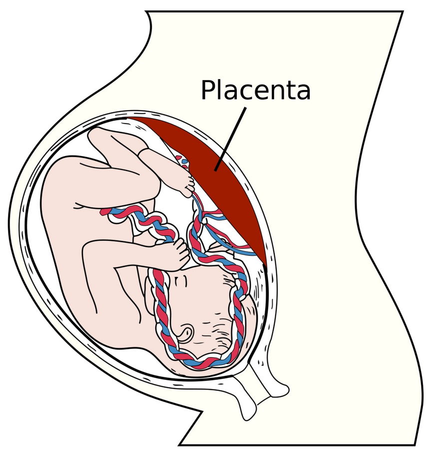
Consistency Regularization Improves Placenta Segmentation in Fetal EPI MRI Time Series

Y. Liu, N. Karani, N. Dey, S. Mazdak Abulnaga, J. Xu, P. Ellen Grant, E. Abaci Turk, and P. Golland

Motivation and problem



Value of 3D placenta segmentation
- Placental biomarker
- Visualization for monitoring and assessment
- Intervention planning

Challenge: labeling of 3D segmentation is expensive
- Large deformations caused by maternal breathing, contractions, and fetal motions.
- Functional EPI images have a lower in-plane resolution and more artifacts

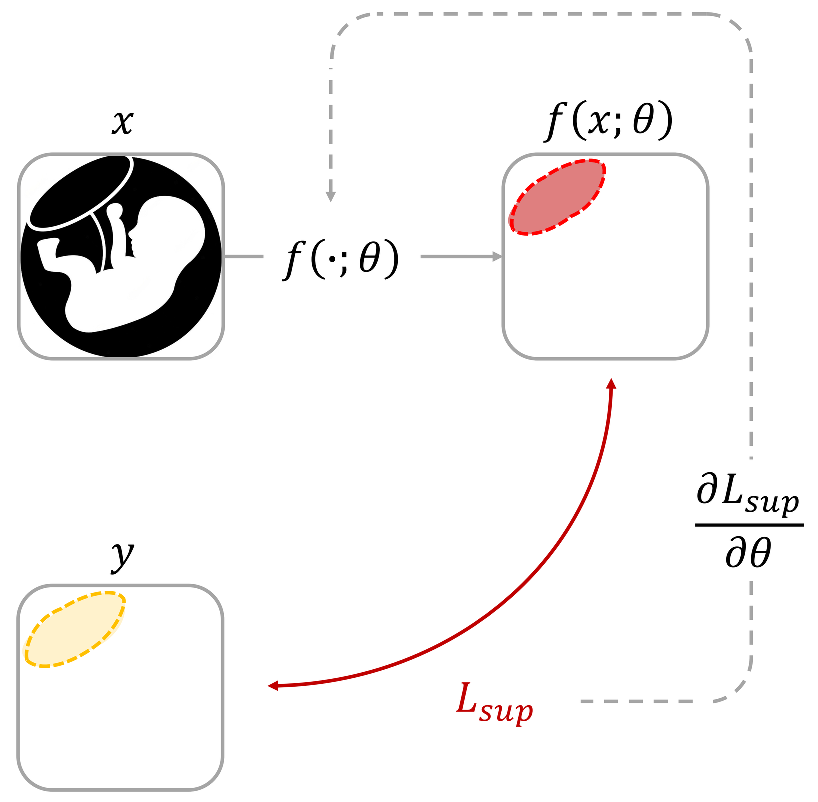
Our solution and contribution

Solution: Semi-supervised learning (SSL) to leverage unlabeled data and minimize the need of labeled data

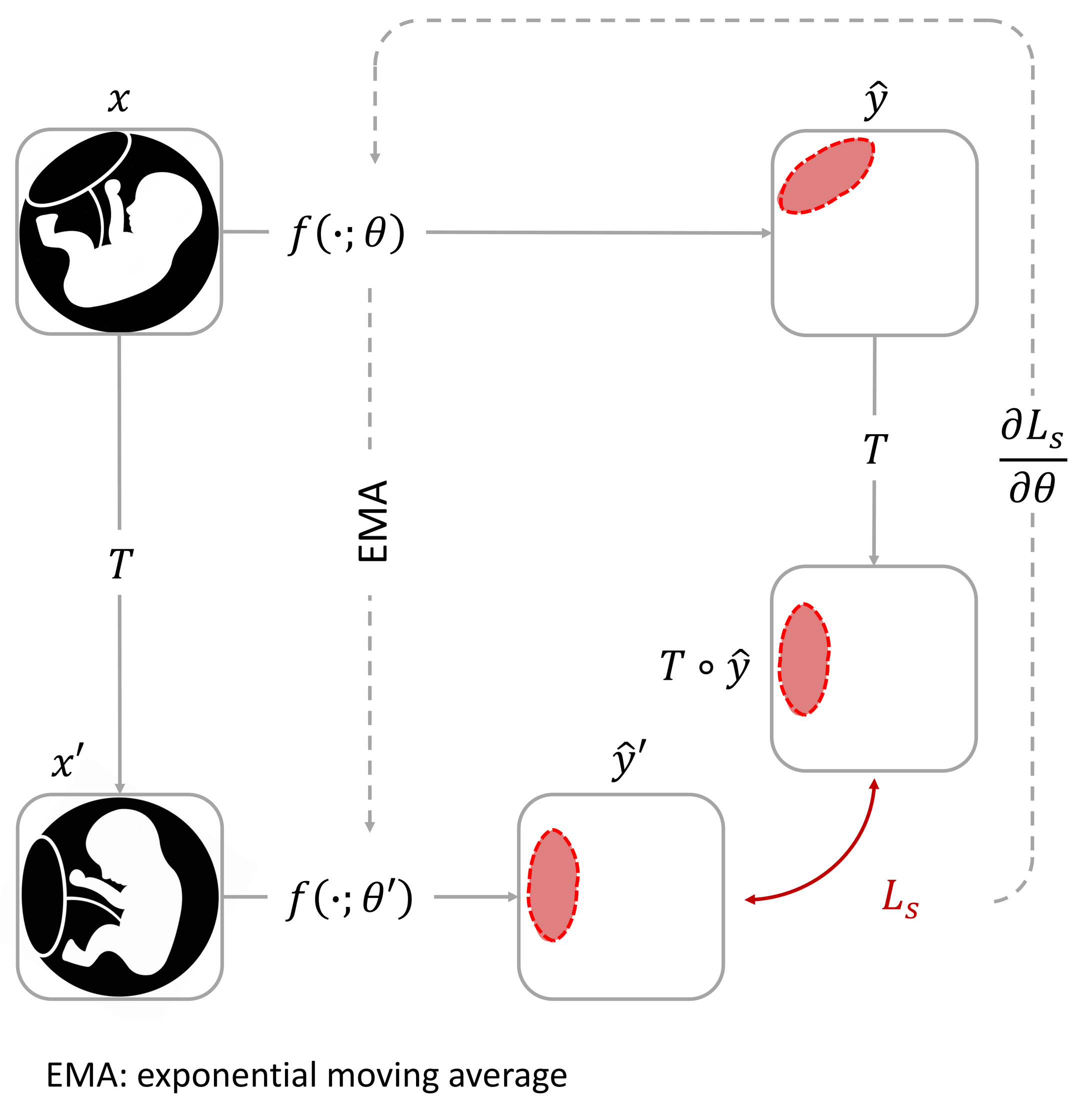
Contributions:
- a consistency regularization methods that leverages the spatial and temporal characteristic of EPI time series data
- the proposed method improves the accuracy and temporal coherency of segmentation and robustness against hard samples.

Method: spatial-temporal consistency regularization

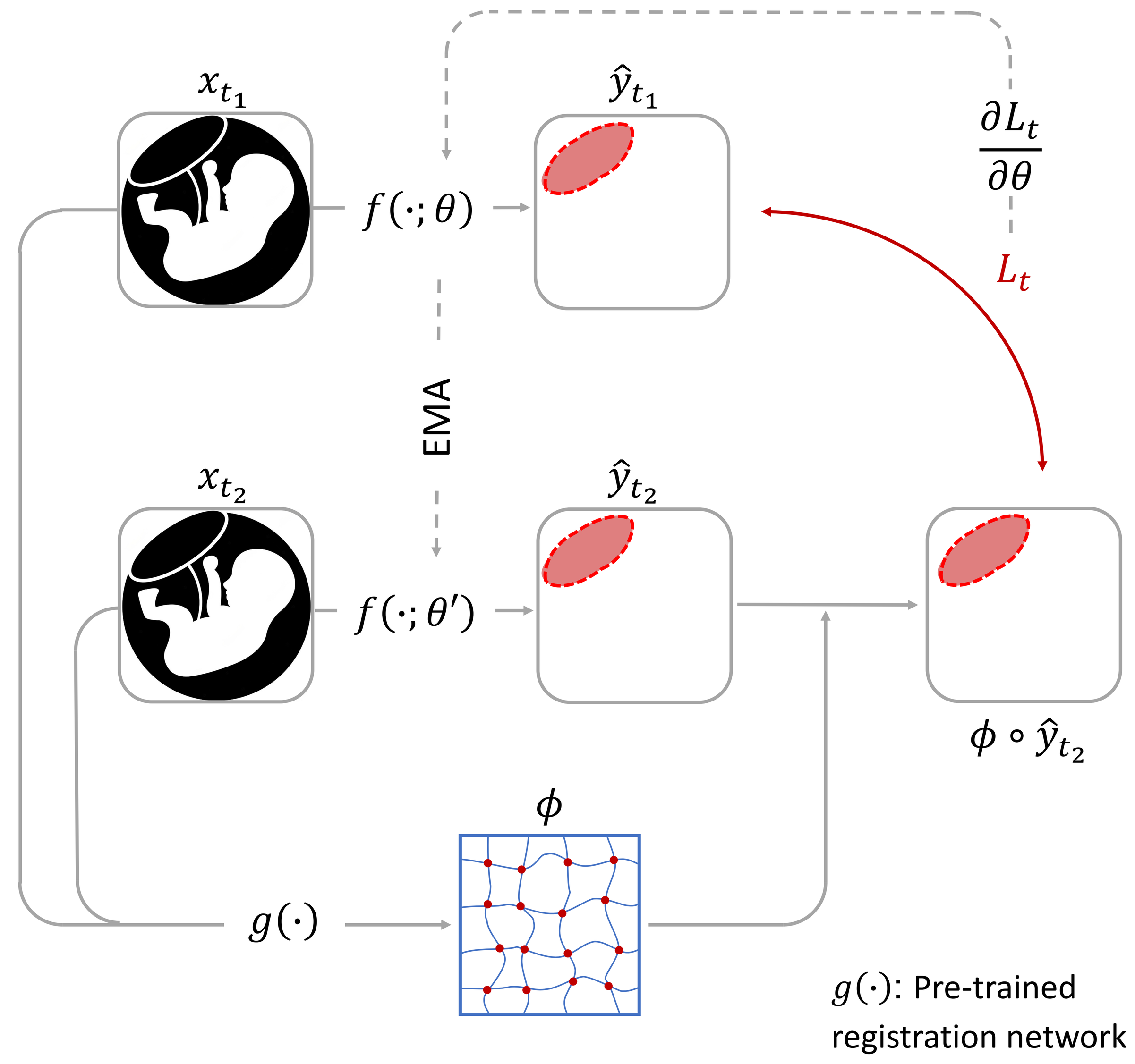
High-level idea: regularize segmentation model to be equivariant to geometry transformations and invariant to intensity transformations.



Supervised loss $f(x;\theta) \Leftrightarrow y$



Spatial Consistency
$T \circ f(x;\theta) \Leftrightarrow f(T \circ x;\theta)$



Temporal Consistency
$f(x_1;\theta) \Leftrightarrow \phi(x_1,x_2) \circ f(x_2;\theta)$

Experiments

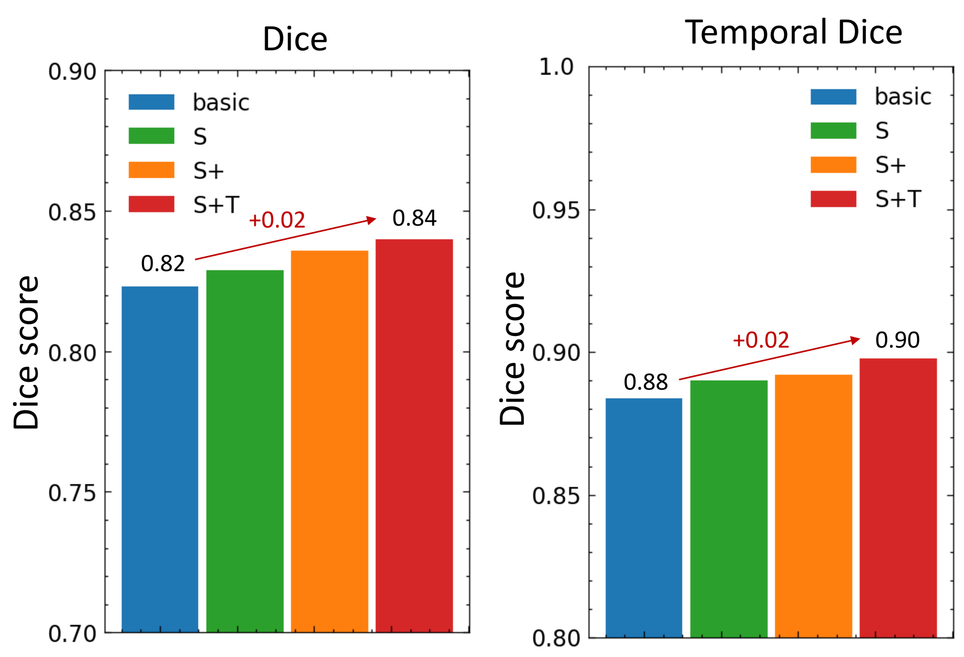
Dataset: 91 subjects. Median length of 216 frames per subject. Between 1 to 6 frames are manually segmented.

Metrics: Dice and Temporal Dice

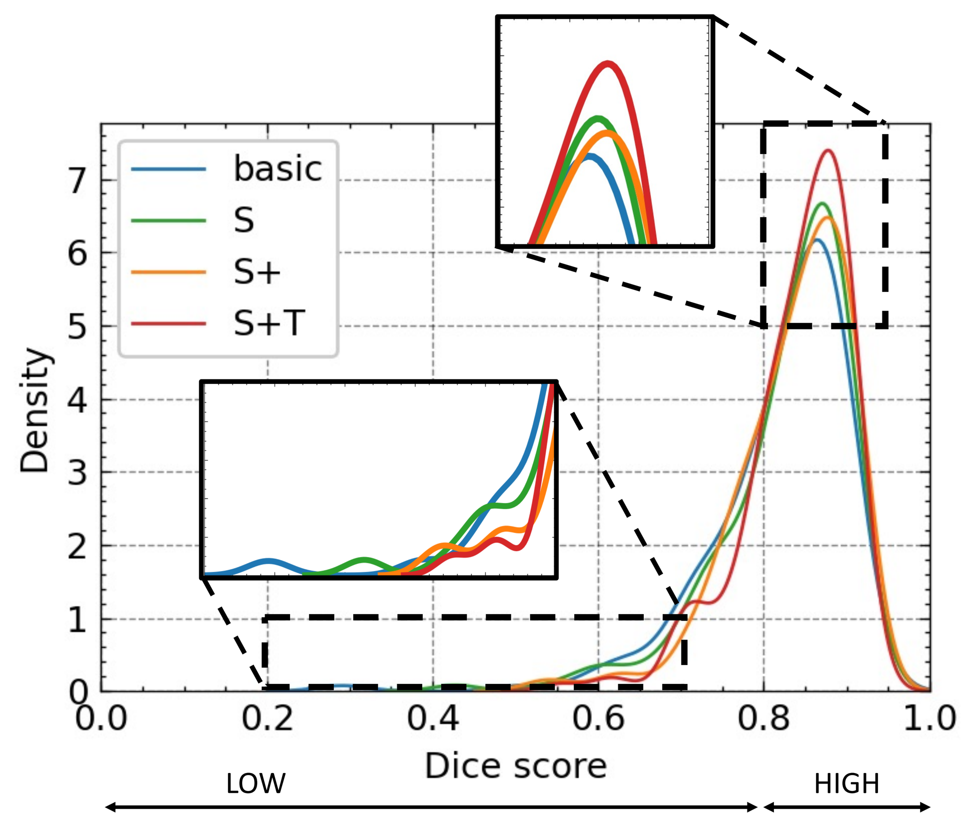
Implementation details: We used DiceCE loss for supervised loss. We used cross validation to determine the weights for each loss and report the best performing results.

Training settings:

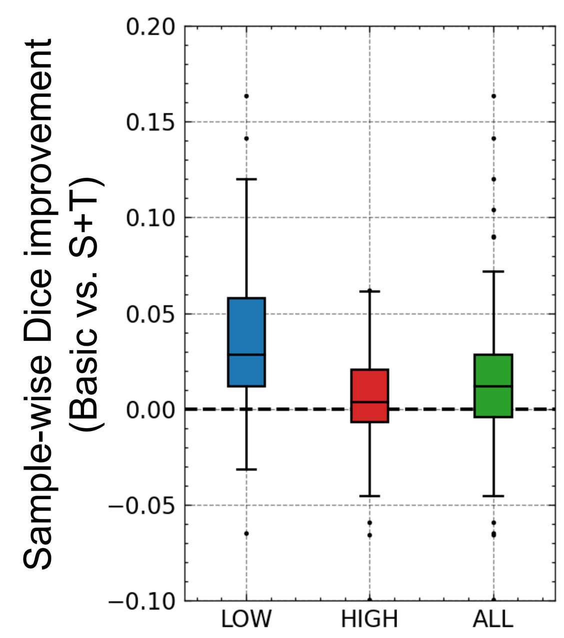
	loss	data
Basic	Sup.	Labeled
S	Sup. + Spatial	Labeled
S+	Sup. + Spatial	Labeled + Unlabeled
S+T	Sup. + Spatial + Temporal	Labeled + Unlabeled



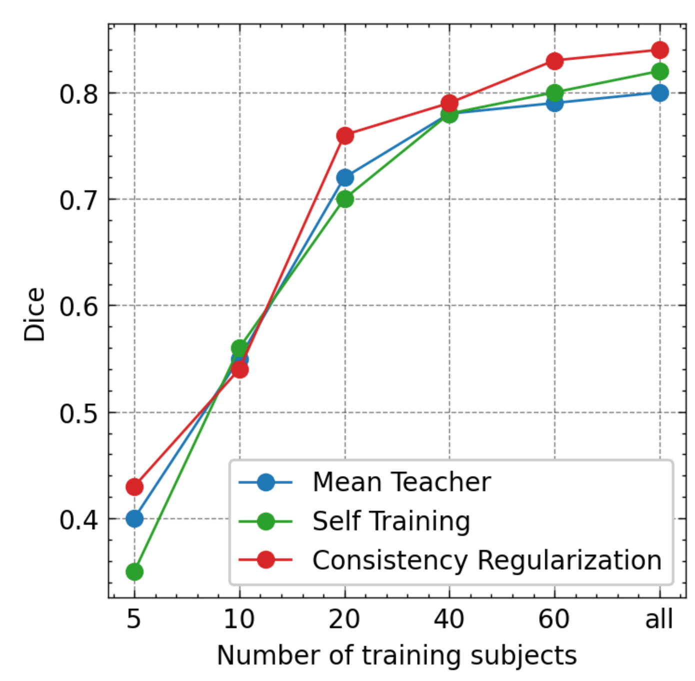
Results 1: improvement in accuracy and coherency of segmentation



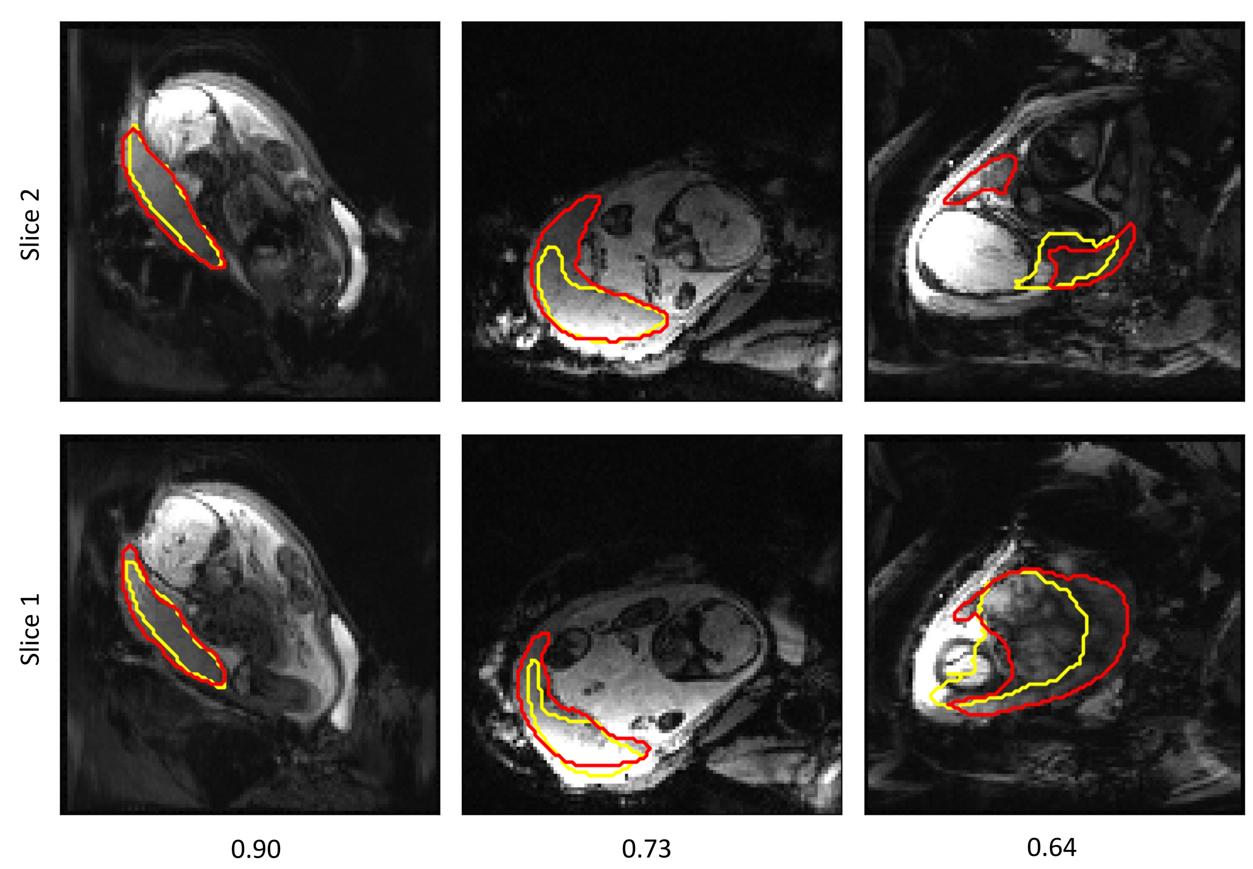
Results 2: tighter mode and smaller long-tail in test Dice distribution



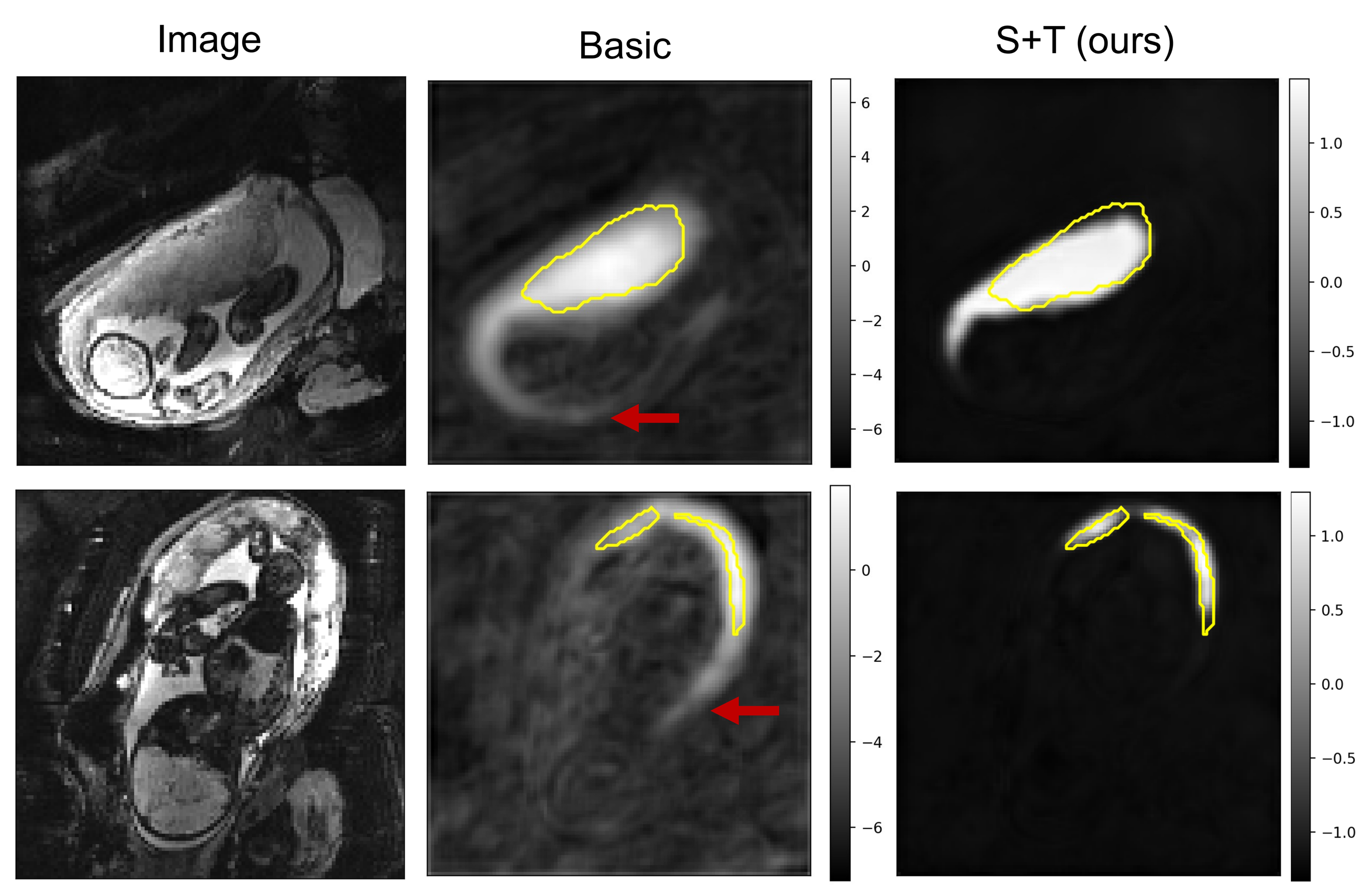
Results 3: more improvement in hard samples



Results 4: better sample efficiency than other SSL methods



Results 5: sample predictions (ground truth in yellow, prediction in red)



Results 6: regularized model has cleaner logits map

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